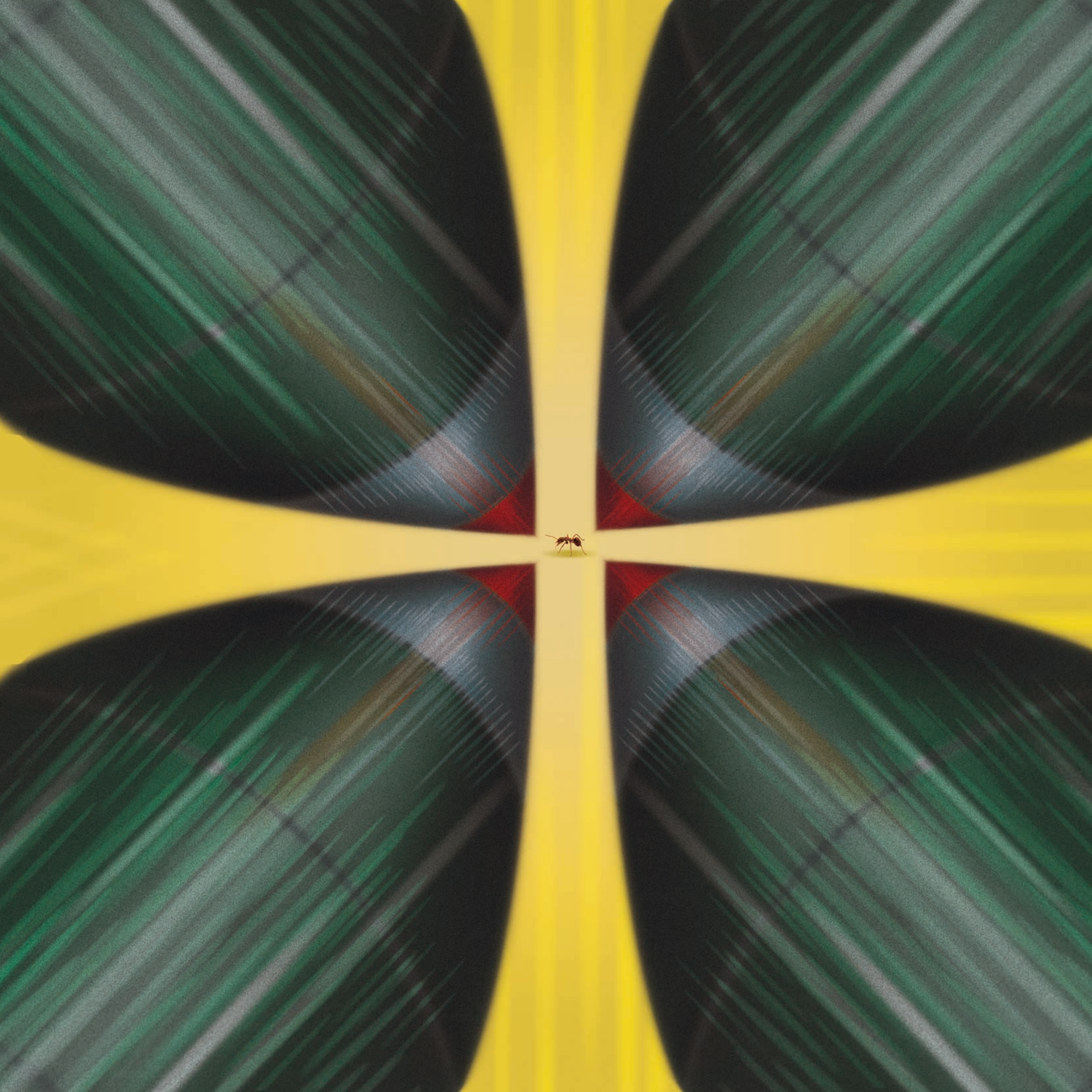
PORTFOLIO RISK – BEYOND VOLATILITY

CURRENTLY APPLIED PORTFOLIO PERFORMANCE MEASURES RELATE THE PORTFOLIO RETURN TO THE RISK FACTOR VOLATILITY OR THE RISK FACTOR CORRELATION. IN THIS STUDY, GUNTER MEISSNER, RANJAN BHADURI, LENNY LINSKY, AND ELEANOR YUAN QUANTIFY ADDITIONAL RISKS, WHICH ARE RELEVANT FOR ASSESSING A MANAGER'S RISK-ADJUSTED RETURN (I.E., CREDIT RISK, OPERATIONAL RISK, LIQUIDITY RISK, AND CORRELATION RISK).



No one cause. Lots of blame to attribute. — Richard Thaler on the reasons for the 2008 global financial crisis

Currently applied portfolio performance measures relate the portfolio return to the risk factor volatility (see Treynor, 1965; Sharpe, 1966; Sortino, 1994) or the risk factor correlation (Meissner, 2019a). In this study we quantify additional risks, which are relevant for assessing a manager's risk-adjusted return (i.e., credit risk, operational risk, liquidity risk, and correlation risk). We derive a "total risk ratio," which relates a manager's performance to the aggregate risks. We derive benchmarks for each risk type so that a portfolio manager can relate each risk type as well as the total risk of her portfolio to these benchmarks.

Types of risk which constitute total risk

In our study, we differentiate five types of risk:

1. *Market risk*, i.e., the risk of price or rate change, which may be quantified by the degree of portfolio volatility, or its extensions VaR (value at risk) or ES (expected shortfall).
2. *Credit risk* (also termed default risk), i.e., the risk that a counterparty does not meet its contractual obligations. Credit risk may be quantified by the credit spread or the credit rating of institutions.
3. *Operational risk*, which is a low-frequency/high-impact risk, therefore difficult to quantify and forecast. In this study we follow the Basel III approach to quantify operational risk (see BCBS, 2017a; BIS, 2019).

These three classical risk categories were the most applied risk categorizations before the 2008 global recession, see for example Hull (2006), Jorion (2006), and the Basel II equation (10) below. However, liquidity risk, categorized within market risk before the 2008 crisis, was a major contributor to the 2008 crisis. Therefore, today, liquidity risk is typically recognized as a separate category, see for example Crouhy and Galai (2014), Hull (2018), Miller (2018), or Meissner (2019b). Hence, we categorize liquidity risk as a separate risk category:

4. *Liquidity risk*, which consists of market liquidity risk, which can be quantified by trading volume or size of the bid–ask spread, and funding liquidity risk, which may be quantified by the current ratio (i.e., current assets/current liabilities).

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During the 2008 crisis, correlations within and between the risk types increased dramatically and were a main reason for the severity of the crisis. Therefore, the Basel III accord includes numerous correlation parameters between and within the risk types to derive the risk capital charge, see BCBS (2015b, 2016, 2019) and the section entitled "Relative risk significance" below. To address systemic portfolio risk, we will include correlation risk as an additional risk type:

5. *Correlation risk*, which is the risk that asset return correlations change unfavorably. We quantify correlation risk by deriving the average coefficient of determination (the square of the correlation coefficient) of the asset returns of the portfolio. The higher the correlation between the asset returns, the higher is the systemic risk, since in a crisis many of the assets are expected to decline jointly.

This article is structured as follows: we introduce the total risk ratio and its risk components, then quantify the individual risk, discuss the relative risk significance and the risk weighting, and calculate the total risk ratio of a sample portfolio, followed by a concluding section.

The total risk ratio

Currently applied portfolio performance measures relate the excess return to the risk measure volatility, as in the still today most widely applied portfolio performance measure, the Sharpe ratio:

$$\text{Sharpe ratio} = \frac{\mu_P - r}{\sigma_P} \tag{1}$$

where

μ_P = return of the portfolio
r = risk-free interest rate
σ_P = volatility of the portfolio.

Numerous extensions of the Sharpe ratio exist, the most prominent being the Sortino ratio = $\frac{\mu_P - r}{\sigma_{<T}}$, where $\sigma_{<T}$ is the portfolio volatility below a target T, and the Treynor ratio = $\frac{\mu_P - r}{\beta_{PM}}$, where β_{PM} is the well-known measure for undiversifiable market risk.

Our new portfolio performance measure relates the excess return of the portfolio to presumably all relevant risk factors:

$$\text{Total risk ratio} = \frac{\mu_P - r}{R_T} \tag{2}$$

where R_T = total risk, i.e., a measure of presumably all risks, which can impact the return of a portfolio in the future. In our model we derive total risk R_T by quantifying the five risk types of market risk (MR), credit risk (CR), operational risk (OR), liquidity risk (LR), and correlation risk (COR), weighting them and adding them:

$$R_T = a\ MR + b\ CR + c\ OR + d\ LR + e\ COR \tag{3}$$

with a + b + c + d + e = 1.

We will derive a benchmark for each risk type with an assigned value of 1. Hence the total risk benchmark will be 5.

Quantifying individual risks

In this section we display how we quantify market risk, credit risk, operational risk, liquidity risk, and correlation risk.

We quantify portfolio market risk by portfolio volatility.[1] The volatility of each asset in the portfolio is derived from the standard deviation of returns:

$$\sigma_p = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(r_{i,t} - \bar{r}_i)^2} \tag{4}$$

where

σ_i = volatility of asset i
$r_{i,t}$ = return of asset i, i.e., $r_{i,t} = \ln(S_{i,t}/S_{i,t-1})$, where
S_t = asset price at time t
i = 1, …, m are the assets in the portfolio
$\bar{r}_i$: mean of asset returns.

The individual asset volatility of equation (4) is input into the portfolio covariance matrix C. Portfolio volatility is then derived as

$$\sigma_p = \sqrt{\beta C \beta^T} \tag{5}$$

where

σ_p = portfolio volatility
β = horizontal β-vector of invested amounts (price × quantity)
C = covariance matrix of the asset returns
β^T = transpose of β, i.e., vertical vector of invested amounts (price × quantity).

Portfolio credit risk can be quantified in several ways. First, the Basel II and III credit value at risk (CVaR) approach (BCBS, 2006) can be applied. The core equation, which goes back to Vasicek (1987), is

$$\mathrm{CVaR}(PD(T),\rho,X) = N\left(\frac{N^{-1}[PD(T)] + \sqrt{\rho}\,N^{-1}(X)}{\sqrt{1-\rho}}\right) \tag{6}$$

where

CVaR = credit value at risk, i.e., the maximum loss due to correlated default risk of the assets in the portfolio, for time frame T, with confidence level X
PD(T) = average default probability of the assets in the portfolio
ρ = default correlation coefficient between the assets in the portfolio
X = confidence level
N = cumulative standard normal distribution, and N^{-1} is its inverse.

Portfolio credit risk can also be quantified by the average portfolio credit spread, which is closely related to the CDS spread (see Meissner, 2005 for details). An alternative way to quantify portfolio credit risk is to average the credit ratings of the assets in the portfolio. We will apply this approach in this article.

We follow the Basel III definition of operational risk: "Operational risk is of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk" (BCBS, 2017a).

We derive operational risk individually for each company in the portfolio by applying the Basel III standardized concept (see BCBS, 2017a; BIS, 2019). The core equation is

$$ORC = BIC \times ILM \tag{7}$$

where

ORC = operational risk capital
BIC = business indicator component; corresponds to the income of a company
ILM = internal loss multiplier; a measure for the likelihood of an operational risk event. In particular

$$ILM = \ln\left(\exp(1) - 1 + \left(\frac{LC}{BIC}\right)^{0.8}\right) \tag{8}$$

where

LC = loss component, defined as "15 times the average annual operational risk losses incurred over the previous 10 years" (BCBS, 2017a).

If the business indicator BIC is equal to the loss component LC, then from equation (8) the internal loss multiplier ILM is 1, and from equation (7) the operational risk capital is the just the business indicator component BIC.

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firm will not be able to meet efficiently both expected and unexpected current and future cashflow and collateral obligations without affecting either daily operations or the financial condition of the firm (BCBS, 2008).

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Market liquidity risk can be quantified by the size of the bid–ask spread or by trading volume. Since trading volume data is easily available, we will quantify market liquidity risk by trading volume.

Suddenly everything was highly correlated. — Financial Times, 2008

Correlation risk is the risk that correlations between two or more variables change unfavorably. Correlation risk was highlighted during the Great Recession, when the correlation between many assets, in particular the default correlation between subprime and prime mortgages, increased significantly.

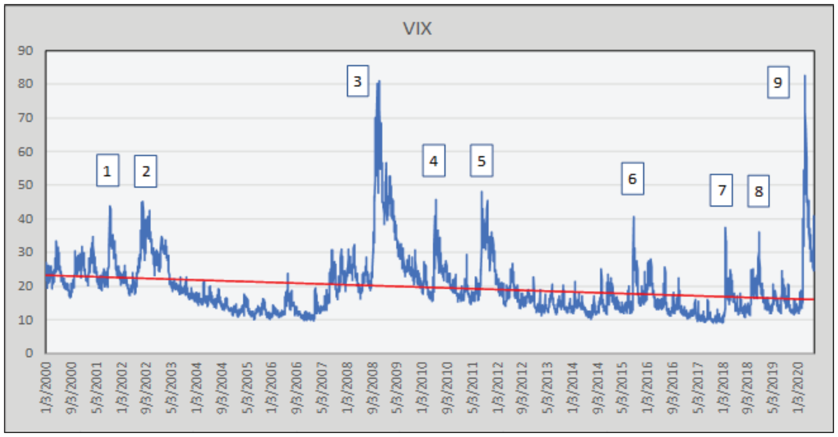
Following Meissner (2019a), we quantify the systemic risk component of correlation with the correlation ratio:

$$\text{Correlation ratio} = \frac{\mu_P - r}{\rho_P^2} \tag{9}$$

where μ_P and r are defined as in equation (1) and ρ_P^2 is the coefficient of determination of the portfolio P, i.e., the square of the Pearson correlation coefficient ρ_P. ρ_P^2 is derived via

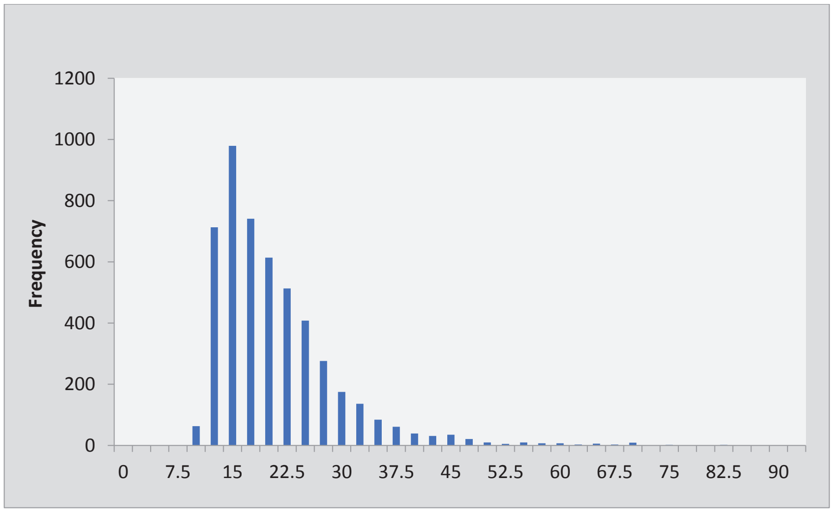
$$\rho_P^2 = \frac{1}{n-1} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j\neq 1}}^{n} w_i \, \rho_{ij}^2 \tag{10}$$

Figure 1: The VIX from 1/3/2000 to 9/1/2019



1: 9/11 terrorist attack, 2: 2002, height of dot-com bubble, 3: 2008, global financial crisis, Dow drops 54 percent, 4: 5/20/2010, Dow drops 376 points on EU debt fears, 5: Black Monday 8/8/2011, US loses its AAA rating from S&P, Dow drops 635 points, 6: 2015, China market crash of 38 percent, 7: February 2018, trade war and interest rate fears, 8: January 2019, recession fears, 9: coronavirus shock.

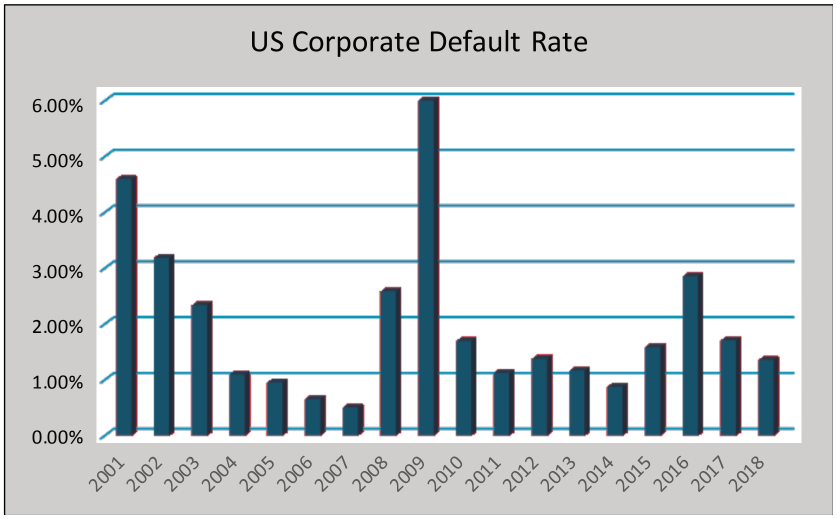
Figure 2: Histogram of the VIX, data from 1/1/2000 to 9/01/2019



where ρ_P^2 is the weighted average of the upper triangle of the coefficient of determination matrix of the asset returns in portfolio P, not including the 1s on the diagonal; w_i is the relative weight of asset i in the portfolio, $\Sigma_{i=1}^{n} w_i$, i.e., w_i is the price times quantity of asset i as a percentage of total portfolio value.

Many [of the risk factors] *are interrelated in that they are relevant in conjunction with others.* — Elena Carletti on the association of risk factors during the global financial crisis

Figure 3: US Corporate Default Rate of Rated Companies from 2001 to 2018. Source: S&P Global Fixed Income Research



Weighting of the risks

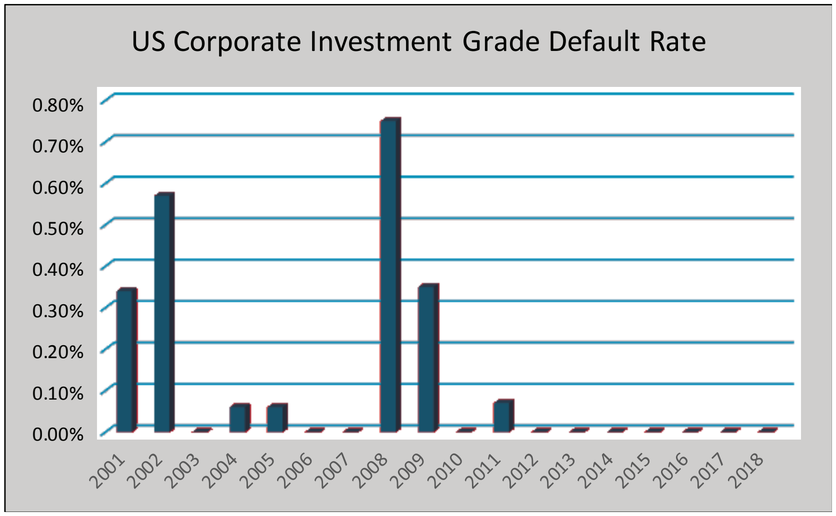
As stated in equation (3), total risk is derived as $R_T = a\,MR + b\,CR + c\,OR + d\,LR + e\,COR$, where $a + b + c + d + e = 1$.

The weighting of the risks, i.e., determining the numerical values for a, b, c, d, e, will be done with respect to (1) the probability of risk occurrence, (2) the risk significance (i.e., the magnitude), and (3) the correlation between the risks.

Market risk

As discussed in the previous section, we quantify market risk by volatility. Figure 1 shows the ex-post occurrence and the significance of stock price volatility, expressed by the VIX.

Figure 4: US investment-grade corporate default rate of rated companies from 2001 to 2018. Source: S&P (2019)



The average of the VIX from 1/3/2000 to 9/1/2019 was 19.57, the standard deviation was 8.51. A one-standard-deviation event occurred on 12.23 percent of all days, a two-standard-deviation event on 4.22 percent of all days, and a three-standard-deviation event on 1.72 percent of all days. No four-standard-deviation events occurred.

Figure 2 displays the VIX histogram, which shows the strong positive skewness, which is 2.16. The 95th percentile captures VIX values only up to 35.09 and the 99th percentile value only up to 52.64, i.e., high confidence levels are misleading since they do not capture rare but significant outliers.

A one-standard-deviation event occurred in 2001 and 2009 (in 11.11 percent of all years). A two-standard-deviation event occurred in 2009 (in 5.56 percent of all years). No three-standard-deviation events occurred

Hence skewness risk exists. The kurtosis of the VIX distribution is a high 10.43. Hence kurtosis risk exists.

Credit risk

Figure 3 shows the ex-post occurrence and the magnitude of credit risk, expressed as the percentage of defaults of US rated companies.

The average annual default rate of rated companies from 2001 to 2018, which included the 2001/2002 dot.com crisis as well as the 2007–2009 global recession, was a modest 1.98 percent. The standard deviation was 1.44 percent. A one-standard-deviation event occurred in 2001 and 2009 (in 11.11 percent of all years). A two-standard-deviation event occurred in 2009 (in 5.56 percent of all years). No three-standard-deviation events occurred. Skewness was 1.40 and kurtosis 4.20.

The average default rate of investment-grade companies is displayed in Figure 4.

The average annual default rate of investment-grade companies from 2001 to 2018 was a low 0.12 percent. The standard deviation was 0.23 percent. A one-standard-deviation event occurred in 2001, 2008, and 2009 (in 16.67 percent of all years). A two-standard-deviation event did not occur. Skewness was 1.63 and kurtosis 4.32. Considering that for regulatory reasons many mutual funds are required to only hold investment-grade bonds, credit risk for these types of mutual fund is rather low.

Naturally, portfolios exposed to speculative-grade bonds assume higher

Table 1: Widening of the bid–ask spread after a drop in the average price S

|Δ Bid| > |Δ Ask| for ΔS < 0 for 30 Dow bonds	Success rate
1-second lag	93.33%
10-second lag	90.00%
30-second lag	96.67%
60-second lag	100%

Notes:
Data from 50 million bid–ask prices from 30 Dow component bonds.
Δ = percentage change.
"1-second lag" means a widening of the bid–ask spread 1 second after the price drop, etc.

default risk: the average annual default rate of speculative bonds from 2001 to 2018 was 4.04 percent with a standard deviation of 3.06 percent. A one-standard-deviation event occurred in 2001, 2002, and 2009 (in 16.67 percent of all years). A two-standard-deviation event occurred in 2001 and 2009 (in 11.11 percent of all years). No three-standard-deviation events occurred.

Operational risk also contributed to the global financial crisis of 2007–2009. Loan officers forged the loan applications of subprime mortgagors, constituting criminal risk, a type of operational risk

Operational risk

As mentioned above, we quantify operational risk on a company level with the Basel III approach of equations (7) and (8).

Operational risk is a low-frequency/high-impact risk. Accounting fraud and criminal conduct, special types of operational risk, typically result in a high company impact. Prominent examples are the Bernie Madoff Ponzi scheme with accumulated liabilities of about \$64 billion and 4,800 deprived clients. The Enron accounting scandal, not detected by the auditing firm Arthur Anderson (now Accenture), led to \$74 billion in losses and Enron employees missing billions of dollars in pension benefits. Both companies naturally dissolved.

Operational risk also contributed to the global financial crisis of 2007–2009. Loan officers forged the loan applications of subprime mortgagors, constituting criminal risk, a type of operational risk.

Legal costs are one of the most significant operational costs. We investigated the 10-K statements of all Dow 30 stocks from 2009 to 2019. The average legal cost per company per year, including legal liabilities, legal expenses, legal fees, and legal defense reserves, was a staggering \$794 million. 26 of the 30 Dow companies reported material legal costs (see Table 4 in Appendix A for details).

Liquidity risk

We will concentrate on market liquidity risk, as mentioned above, since funding liquidity risk is highly related to credit risk.

Market liquidity risk can be quantified by the size of the bid–ask spread. In a study with 50 million bid and ask prices for 30 bonds, each from one Dow component, Engle et al. (2019) find that a decrease in the average price of the bonds leads to a significant widening of the bid–ask spread. The results are given in Table 1.

Regression results confirm Table 1, with significant p and β values for price declines, but insignificant values for price increases (see Engle et al., 2019).

A second way to measure market liquidity risk is trading volume. The higher the trading volume of an asset, typically the higher the liquidity (i.e., the ability to eliminate a position without market disruption). In particular, studies by Amaral (2010), Crowely and Luo (2011), and Musto et al. (2015) show a significant decline in trading volume during times of crisis. We derive the average daily trading volume as a benchmark for risk managers.

Correlations always increase in stressed markets. — John Hull

Correlation risk

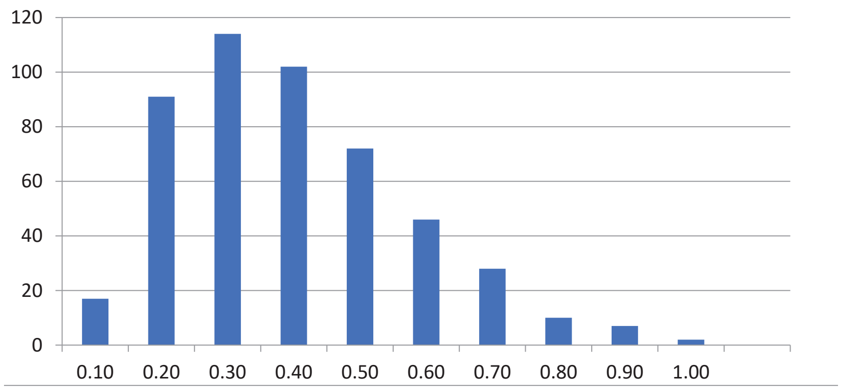
As mentioned in in the previous section, we quantify correlation risk with the correlation ratio of equation (9) and the coefficient of determination of equation (10). Correlation risk has a systemic component, as shown in Table 2.

Table 2: The correlation level is derived as the average Pearson correlation coefficient of 30×30 Dow monthly stock return bins (the ones on the diagonal were eliminated). Data from 1972 to 2019

	Correlation level	Correlation volatility
Expansionary period	27.46%	71.17%
Normal economic period	33.06%	83.06%
Recession	36.96%	80.48%

Table 2 displays the higher correlation level in distressed times. Table 2 also displays the higher correlation volatility in normal economic periods compared to expansionary periods. We expected higher correlation

Figure 5: Correlation histogram of Dow stock returns



volatility in times of recession. However, correlation volatility in recessions seems to plateau at a relatively high level. Figure 5 shows the correlation histogram.

Figure 5 displays the somewhat lognormal distribution of monthly Dow stock return correlations. A one-standard-deviation event occurred in 16.45 percent, a two-standard-deviation event in 3.84 percent, and a three-standard-deviation event in 0.55 percent of all cases. No four-standard-deviation events occurred. Skewness and kurtosis were rather moderate at 0.71 and 0.34, respectively.

Relative risk significance

With respect to relative risk significance, volatility (which we use to quantify market risk) played a key role in the 2007–2009 global financial crisis. The Basel Committee states that "roughly two-thirds of losses attributed to counterparty credit risk were due to CVA losses and only about one-third were due to actual defaults" (B IS, 2011). Hence it may seem prudent to weight market risk higher than credit risk in times of crises. However, defaults can have a critical impact, as in September 2008, when Lehman Brothers defaulted. As a consequence of the default, stock markets worldwide collapsed, and credit markets were virtually frozen. Even as the FED guaranteed interbank loans, lending resumed only very slowly and gradually.

Financial institutions allocate about 65 percent of the risk capital to credit risk, 20 percent to operational risk, and 15 percent to market risk. Would this be a guide for weighting the risks above? The answer is no, since banks often hedge their exposure, which is easiest for market risk, hence the market risk capital allocation is quite low. However, most mutual fund managers typically go long the assets without significant delta-hedging.

With respect to risk weighting, the capital adequacy ratio in Basel II was derived as

$$\frac{\text{Total Capital (Tier 1+Tier 2)}}{\text{Credit Risk+12.5}\quad\text{(Market Risk+Operational Risk)}} \geq 8\% \tag{11}$$

where the denominator determined the risk-weighted assets (RWA). Hence the Basel Committee weighted market risk plus operational risk significantly higher than credit risk. However, after the 2007–2009 crisis, risk-weighted assets are derived in a different way:

$$\text{RWA} = \text{K} \times 12.5 \times \text{EAD} \tag{12}$$

where K is the capital requirement, derived from a fairly complex equation which includes loss given default (LGD), probability of default (PD), default correlation between the assets (R), and a maturity adjustment (b). EAD is the exposure at default. For details, see BCBS (2013) and BCBS (2015a, 2019).

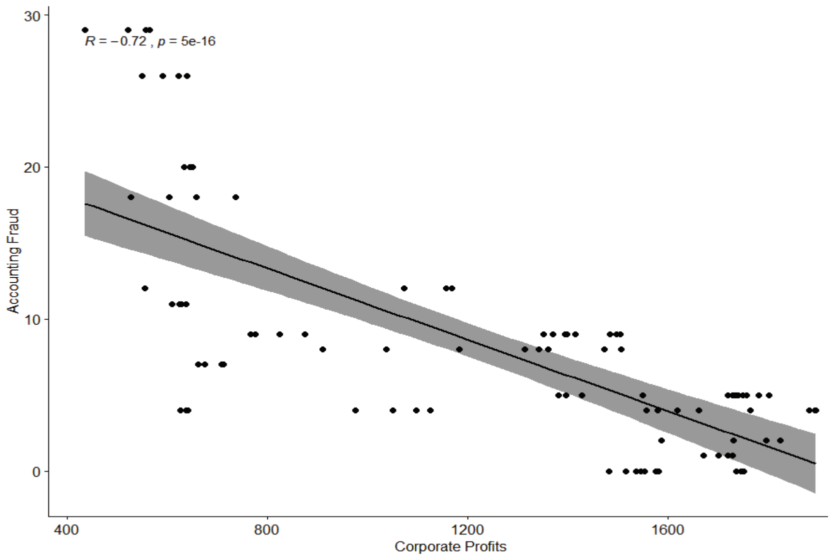
Weighting the risks is complex, since the risks are related. For example, if an asset declines (market risk), credit risk (i.e., default risk) and illiquidity of the asset typically increase. In addition, correlation between assets typically increases in times of crisis, as pointed out earlier.

The risk causality can be bi-directional: a market decline may cause higher credit risk and illiquidity, as well as increasing credit risk, and illiquidity may cause a market decline. The Basel Committee (BCBS, 2016) in its document "Minimum requirements for market risk" includes a "jump-to-default (JTD) risk charge," highlighting the close relationship between market risk and credit risk. Operational risk causality is typically one-directional though: operational risk may be the cause for market risk and credit risk to increase, but is seldom the effect of other risks.

It may seem prudent to weight operational risk relatively high due to its "stand-alone" nature, i.e., generally low correlation with other risks when it is the dependent variable (so the possible effect). However, being the cause, operational risk has a high impact, i.e., high correlation with all other risks. For example, the discovery of accounting fraud will typically lead to a sharp decline in stock price and an increase in default probability. Nevertheless, detrimental operational events are very rare. In the last 20 years, of the 3,670 ▷

Financial institutions allocate about 65 percent of the risk capital to credit risk, 20 percent to operational risk, and 15 percent to market risk. Would this be a guide for weighting the risks above?

Figure 6: Accounting fraud with respect to corporate profits from 1996 to 2019. $R^2 = 0.3303$, $\beta = -0.20$



US listed companies only 19 filed for bankruptcy following accounting fraud. Of those 19, 9 dissolved.

An interesting question is whether operational risk increases in an economic crisis, and hence has some indirect correlation with other risks. The answer depends on the type of operational risk. Nature catastrophes such as hurricanes and tsunamis are naturally not related to economic crises. However, does corporate crime, in particular accounting fraud, increase in distressed times? That is, are managers more inclined to "cook the books" in an economic crisis when profits typically deteriorate? In our study of 95 US and international fraud cases from 1996 until 2019, we regressed accounting fraud against the explanatory variables of GDP and corporate profits. We found some evidence that accounting fraud is more prevalent when profits are lower, as seen in Figure 6.

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Regressing accounting fraud with respect to real GDP gives similar, although slightly less significant, results, as seen in Figure 7 in Appendix B. In the future, operational risk may increase in significance due to increased cyber and hacking attacks.

With respect to the significance of correlation risk, the Basel Committee recognizes: "As the recent crisis [the Great Recession 2008] demonstrated, reliance on historical correlations … in the market risk metric may materially underestimate 'true' risk in certain cases" (BCBS, 2013). As a consequence, the Basel accord now includes numerous Pearson cross-correlations between six risk types: (1) equity risk, (2) interest rate risk, (3) foreign exchange risk (FX), (4) counterparty credit spread risk, (5) reference credit spread risk, and (6) commodity risk. In addition, cross-bucket correlations between risk factors such as the yield curve and inflation rate, interest rate volatilities and inflation volatilities, or FX delta and vega risks are now part of Basel III (BCBS, 2015).

In addition, the capital charge K for the calculation of unhedged CVA includes correlation between systematic and idiosyncratic risk:

$$K_{spread}^{unhedged} = \sqrt{\left(\rho \sum_{c} S_c\right)^2 + (1-\rho^2)\sum_{c} S_c^{\,2}} \tag{13}$$

where

S_c = the exposure at default (EAD) over all derivatives netting sets with counterparty c

ρ = the Pearson correlation between the credit spread of counterparty c and the systematic factor.

The first term on the right-hand side of equation (13) represents systematic risk, the second term on the right-hand side represents idiosyncratic risk.

Furthermore, for hedged credit spreads, banks must include the correlation between the counterparty c and the hedging entity h, r_{hc}, in the calculation of the capital charge for the credit spread. This results in a rather complicated equation:

$$K_{spread} = \sqrt{\left[\rho \sum_{c}\left(S_c - \sum_{h \in c} r_{hc} S_h^{SN}\right) - \sum_{i} S_i^{ind}\right]^2 + (1-\rho^2)\sum_{c}\left(S_c - \sum_{h \in c} r_{hc} S_h^{SN}\right)^2 + \sum_{h \in c}(1-r_{hc}^2)(S_h^{SN})^2} \tag{14}$$

where

S_c and ρ are defined as in equation (13)

$h \in c$ = hedges with counterparty c

r_{hc} = Pearson correlation between the credit spread of counterparty c and the credit spread of a single-name hedge h

S_h^{SN} = price of a single name (SN) hedge, weighted by the Basel accord with respect to the risk of sector, ranging from 4.1 to 10.2 percent for investment-grade counterparts

S_i^{ind} = price of index hedge i.

In equation (14) the first term on the right-hand side represents the systematic factor, the second term the idiosyncratic factor, and the third term ensures that the capital charge is positive in case of indirect hedges.

In conclusion, a risk manager may choose her own risk weighting. While

Table 3: Portfolio risk values and total risk RT of the equally weighted portfolio

Risk type	Benchmark	Portfolio value	Portfolio risk value
Market risk (MR)	19.57%	18.36%	0.9521
Credit risk (CR)	BBB+	AA	0.6938[a]
Operational risk (OR)	$11,665,106,081	$8,000,683,275	0.6859
Liquidity risk (LR)	16,020,497	13,931,947	1.1304
Correlation risk (COR)	32.38%	9.03%	0.2789
Total risk value R_T			3.7411

[a] We applied Fitch's 24-scale long-term rating system and assigned equal-distance values between 0 and 1 to each credit rating.

credit risk, operational risk, liquidity risk, and correlation risk may have a lower frequency than volatility risk, they typically have a high impact. Therefore, we believe equal risk weighting is a reasonable approach.

Sample calculation of the total risk ratio

In this section we calculate the total risk ratio for a 10-asset portfolio consisting of the equally weighted positions (1) Cash, (2) 10-year Treasury Bond, (3) DIS, (4) HD, (5) INTC, (6) JNJ, (7) KO, (8) MCD, (9) WMT, and (10) XOM. The total risk ratio can also be applied to exchange traded assets or a portfolio including derivatives.

For each risk, i.e., market risk (MR), credit risk (CR), liquidity risk (LR), operational risk (OR), and correlation risk (COR), we derive a benchmark and compare the specific portfolio risk type to this benchmark. If the specific portfolio risk is equal to the benchmark, a value of 1 will be assigned. Therefore, if all risks MR, CR, LR, OR, and COR are equal to their benchmark, following equation (3), the total risk of the portfolio R_T will be 5.

While credit risk, operational risk, liquidity risk, and correlation risk may have a lower frequency than volatility risk, they typically have a high impact

If the value of the portfolio risk is higher than the benchmark, a proportionally higher portfolio risk value will be assigned, and vice versa. For example, to derive the market risk value MR for the portfolio, let's assume that the VIX is 20 percent and the portfolio volatility is 25 percent. Hence the portfolio volatility is 25 percent higher and the portfolio market risk value would be $1 + 1 \times 0.25 = 1.25$.

We derived the following benchmarks from historical data. For market risk, the average VIX from 2009 to 2019 was 19.57. For credit risk, the average rating of the S&P 500 companies is BBB+, and BB for US companies overall (see S&P, 2015). For operational risk, we investigated the 10-K statements for the Dow 30 stocks for the last 10 years. Following equations (7) and (8), the average annual operational risk ORC for the Dow 30 stocks was $11,665,106,081. With respect to liquidity risk, the average daily trading volume of the Dow 30 stocks for the last 10 years was 16,020,497. For correlation risk, the average monthly correlation of Dow stock returns from 1972 to 2019 was 32.38 percent.

The total risk ratio for the equally weighted (1) Cash, (2) 10-year Treasury Bond, (3) DIS, (4) HD, (5) INTC, (6) JNJ, (7) KO, (8) MCD, (9) WMT, and (10) XOM is summed up in Table 3.

In Table 3 we applied an equal weighting of the risk types. The total portfolio risk value R of 3.7411 is lower than the benchmark of 5 [see equation (3)]. This is an expected result, since we chose a conservative portfolio with 10 percent in cash and 10 percent in Treasury bonds as well as several low-risk consumer staple stocks such as JNJ, KO, MCD, and WMT. The low portfolio correlation risk of 9.03 percent is due to the fact that the cash position has no correlation with the other positions. In addition, the 10-year Treasury Bond had a negative correlation with all other stocks.

The return of the portfolio μ_P was 14.48 percent. With a risk-free interest rate of 1 percent, the total risk ratio of equation (2), total risk ratio = $\frac{\mu_P - r}{R_T}$ results in $\frac{14.48\% - 1\%}{3.7411} = 0.0360$, or 3.60 percent. This result may be compared to the total risk ratio of other portfolios. Naturally, the portfolio performance can be related to each individual risk type to assess a particular risk exposure.

Conclusion

Currently applied portfolio performance measures such as the Sharpe ratio, the Treynor ratio, or the Sortino ratio relate the performance of a manager to the risk factor volatility. First, this is conceptually questionable, since high volatility means high upside potential, which is penalized with these concepts. Second, other types of risk exist. Besides volatility, we quantify the risk types of credit risk, operational risk, liquidity risk, and correlation risk and relate them to a manager's performance.

We derive benchmarks for each risk type, so that an analyst or manager can compare the specific risk type of the portfolio to this benchmark. We introduce a "total risk ratio," which relates a manager's performance to the aggregate of the risks.

We also discuss the significance of the risk types and the interaction between these risks. A risk manager may choose her own risk weighting.

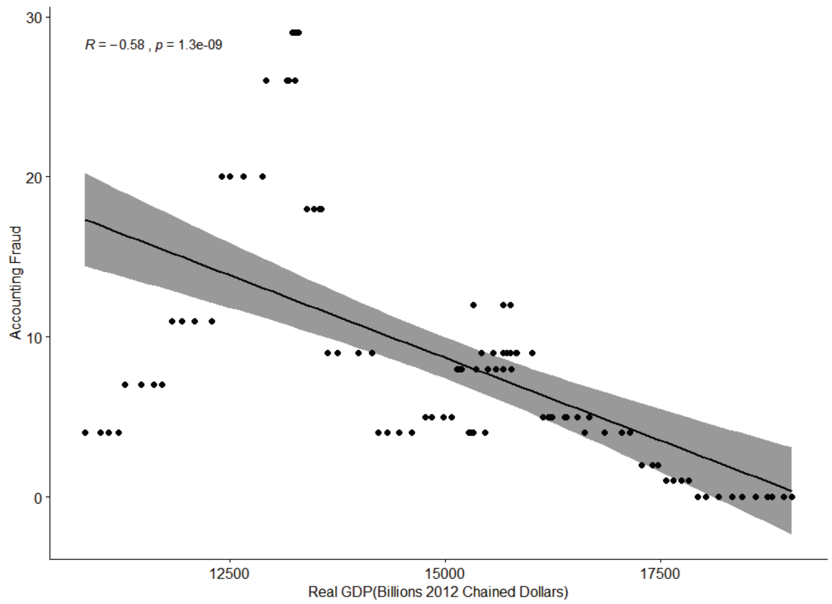
We show how the total risk ratio of a specific portfolio is calculated. We hope that the total risk ratio will enhance risk-adjusted performance evaluation in reality.

Appendix A
Table 4: Annual legal cost for the Dow 30 companies from 2009 to 2019

Average annual legal cost of Dow 30 companies from 2009 to 2019			
Rank	Company	Average cost per year	
1	Dow Chemical	$	6,947,584,906
2	JP Morgan	$	3,453,300,000
3	Goldman Sachs	$	2,600,000,000
4	Chevron	$	2,020,766,667
5	Disney	**$**	**1,110,500,000**
6	JNJ	**$**	**1,100,000,000**
7	Cisco	$	827,339,474
8	Pfizer	$	787,100,000
9	Visa	$	744,200,000
10	Intel	**$**	**698,083,333**
11	IBM	$	667,083,333
12	Microsoft	$	644,000,000
13	United Tech	$	557,300,000
14	Travelers Co Inc	$	444,175,000
15	Amerucan Express	$	436,666,667
16	Merck	$	251,080,000
17	General Electric	$	157,283,000
18	Walmart	**$**	**133,030,600**
19	United Health	$	80,800,000
20	3M	$	66,536,111
21	Home Depot	**$**	**56,750,000**
22	Proctor and Gamble	$	40,306,300
23	Caterpillar	$	5,771,707
24	Exxon Mobile	**$**	**829,847**
25	Verizon	$	468,600
26	Coca Cola	**$**	**145,000**
27	Apple[1)]	$	-
28	Boeing[2)]	$	-
29	McDonalds	**$**	**-**
30	Nike	$	-
	Average	$	794,370,018

Notes:
1. It may seem surprising that APPL did not report any legal cost. However, the SEC states that "no information [for legal cost] need be given if the amount involved does not exceed 10 percent of current assets." https://www.govinfo.gov/content/pkg/CFR-2016-title17-vol3/pdf/CFR-2016-title17-vol3-sec229-103.pdf
2. The compensation for the two 737 MAX crashes of $1.2 million for each of the victims' families will materialize in the 10-K statement after our research period, which ended in December 2019.

Appendix B
Figure 7: Accounting fraud with respect to real GDP from 1996 to 2019. $R^2 = 0.3303$, $\beta = -0.20$



ENDNOTE

1. We quantify market risk by volatility and not the value at risk or expected shortfall concept, since the classical risk measures such as Sharpe ratio, Treynor ratio, or Sortino ratio quantify market risk with volatility, so our approach is comparable with these measures.

About the Authors

After a lectureship in mathematics and statistics at the Economic Academy Kiel, **Gunter Meissner** PhD joined Deutsche Bank in 1990, trading interest rate futures, swaps, and options in Frankfurt and New York. He became Head of Product Development in 1994, responsible for originating algorithms for new derivatives products, which at the time were Index Amortizing Swaps, Yield Curve Swaps, Lookback Options, Quanto Options, and Bermuda Swaptions. In 1995/1996 he was Head of Options at Deutsche Bank Tokyo. From 1997 to 2007 he was Professor of Finance at Hawaii Pacific University and from 2008 to 2013 he was Director of the Financial Engineering Program at the University of Hawaii. Currently, he is President of Derivatives Software (www.dersoft.com) and Adjunct Professor of Mathematical Finance at Columbia University and NYU. He has published numerous papers on derivatives and is a frequent speaker at conferences and seminars. He is the author of seven books, including Economic and Financial Forecasting – 10 Methods (2020). He can be reached at gunter@dersoft.com.

Ranjan Bhaduri is the founder and CEO of Bodhi Research Group, an advisory firm that assists allocators with alternative investments. He has been invited globally to speak on advanced topics in portfolio and risk management. He has held an advisory role at the East–West Center, a leading think-tank on the Asia-Pacific Rim region. He holds both the CFA and CAIA charters.

Lenny Linsky is a recent graduate from the University of Hawaii at Mānoa, with a BA in Economics and a certificate in quantitative methods. Prior to that, he was a professional baseball player and spent 6 years at the Tampa Bay Rays organization. He contributed to this article under the direction of Dr. Gunter Meissner, while taking his Mathematical Economics course.

Eleanor Yuan is an undergraduate student majoring in Economics and Global Environmental Science at the University of Hawaii at Mānoa. She plans to graduate in 2021. Her interests and recent projects involve the application of statistical modeling in economic and environmental issues.

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